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Analysis

Climatic Cost-benefit Analysis Under Uncertainty and Learning on Climate Sensitivity and Damages

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ABSTRACT

Cost-benefit analyses on climate change have drawn considerable critique, primarily due to contestable choices of discounting and high uncertainties in climate sensitivity and climatic damages. Consequentially, it is argued that cost-benefit analysis can suggest mitigation rates that are nearly arbitrary. This article investigates how firm conclusions can be made from cost-benefit analysis if the main uncertainties are considered endogenously in the analysis and an extensive sensitivity analysis is carried out regarding the contestable assumptions.

The SCORE model is used to calculate optimal emission pathways and carbon prices that hedge against climate sensitivity and damage risks using a wide range of plausible parametrizations. In a vast majority of cases the near-term emissions fall between 1.5 °C and 2 °C emission pathways, giving thus support for the Paris Agreement targets. Sequential decision-making allows hedging against uncertainties and readjusting mitigation efforts over time to reflect new information, leading to diverse stabilization temperatures in the long-term. Assumptions on mitigation costs, climate sensitivity and damages affect optimal near-term mitigation and long-term stabilization temperature more strongly than the discount rate choice. The consideration of parametric uncertainty on climate sensitivity and damages adds a substantial risk component to carbon pricing, while learning can induce significant price volatility in a decadal timescale.

1. Introduction

Cost-benefit analysis (CBA) aims to specify the economically optimal strategies for mitigating climate change through minimizing the sum of costs from mitigation action and ensuing climate damages. As such, it could suggest to what level greenhouse gas emissions should be reduced, or how they should be priced at different points of time. The analysis is commonly carried out with integrated assessment models (IAMs), numerical simulation models combining aspects from economics, climate science and technological development.

Past analyses have yielded very differing suggestions on how ambitious the mitigation efforts should be (see e.g. Tol, 2009), rendering the overall conclusions from climatic CBA rather unclear. As a single draw from this lot, the latest incarnation of DICE (Nordhaus, 2017) – perhaps the best-known and highly cited model in this context – yields an optimal policy of limiting temperature increase to levels around 4 °C within the next 200 years. This conflicts starkly with the currently stated aims in global climate policy. The Paris Agreement of the United Nations' climate convention aims to keep global temperature increase "well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C".

However, notable critique has been presented against climatic cost-benefit analysis and IAMs (Weitzman, 2009; Pindyck, 2013; van den Bergh and Botzen, 2015). The most severe argument highlights the limitations of our current knowledge on what impacts climate change might have on ecosystems and the society, including the possibility of a total catastrophe; and how such climate impacts should be valued. Disagreement exists also on how the costs and benefits of different generations should be aggregated (Dasgupta, 2008). Further challenges in this setting arise from uncertainties in climate sensitivity (Knutti and Hegerl, 2008) and the cost of future emission reductions (Rogelj et al., 2013).

The objects of the criticism have very different characteristics. The uncertainty on climate sensitivity is epistemic.[1] Climate damages also carry epistemic uncertainty on the realized impacts, but also involve normative judgments on how the impacts are valued. Discounting involves normative judgement about intergenerational equity. Future mitigation costs entail epistemic uncertainty on what might be physically achievable, but also depend strongly on how much the society invests in developing and deploying new technologies, and therefore this uncertainty cannot be separated from the mitigation action considered in a cost-benefit model.

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[1] However, one should note that the estimation of climate sensitivity involves also aleatory uncertainty, due to the natural variations embedded in observations.

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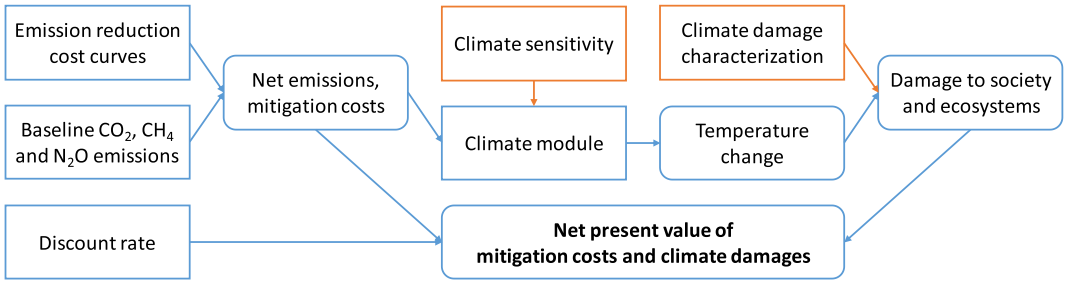


Fig. 1. A graphical outline of the SCORE model. Uncertainty and learning is assumed for the input parameters in boxes with orange outline. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The epistemic uncertainties may be reduced over time through new observations and research, which can be termed 'learning'. However, learning is not inevitable, for example if there exist structural errors or omitted effects in models that explain the phenomenon being investigated (see e.g. Leach, 2007; Oppenheimer et al., 2008). Learning might be even less straightforward with normative judgements with no objective value, such as discounting or the valuation of climate impacts. Therefore the uncertain and contestable elements need to be addressed using different methods in IAMs.

The Paris Agreement targets are more of a safe minimum standard than a result of deliberate CBA (Randalls, 2010). Because the underlying rationale differs, the moderate mitigation level suggested by many CBA studies (e.g. Crost and Traeger, 2014; Nordhaus, 2017) does not entirely refute the Paris Agreement targets as overly ambitious. Yet, some weighing between the achievable level of mitigation, the acceptable level of costs and the benefits from mitigation is required also in the determination of safe minimum standards.

This implicit reasoning is a conceptual problem with safe minimum standards (Crowards, 1998) due to the ambiguity over what are a safe level of climate change and acceptable costs. Formalizing the determination of targets through CBA makes the assumptions and valuations used in the analysis explicit, which facilitates understanding and transparent argumentation regarding the results. This is exactly the reason for the amount of criticism climatic CBA has drawn.

The critique must be nevertheless confronted. In order for CBA to be a usable tool for determining climate targets, it needs to provide some degree of robustness against uncertainty and alternative specifications. A number of analytical and computational approaches allow the consideration of uncertainty when deriving optimal policies (Golub et al., 2014). Also, the sensitivity of the modeling results to alternative parametrizations can be tested for elements for which probabilistic methods are not applicable. This approach can also be used to test alternative characterizations of probability for quantities that have little or no empirical foundation, such as the damages from climate change.

A number of past analyses have sought optimal mitigation strategies under uncertain climate sensitivity (Kelly and Tan, 2015; Hwang et al., 2017) or damages (Kolstad, 1996; Crost and Traeger, 2014). Some earlier studies have assessed these uncertainties jointly, but under a pre-defined set of policy responses (Lave and Dowlatabadi, 1993; Lempert et al., 1996; Yohe, 1996) or by finding non-adaptive strategies under a sampling of uncertain parameters (Plambeck and Hope, 1996). Robust decision approaches have also been used to address climatic responses under limited uncertainty information (Hall et al., 2012).

This paper investigates how well the criticism could be addressed by considering the uncertainties in climate sensitivity and damages within the CBA, and carrying out an extensive sensitivity analysis for the main parameters. An exogenous learning process is assumed to reduce the uncertainties over time. The computational approach finds mitigation strategies that adapt to the new information over time, minimizing the expected value of costs and benefits and hedging against both of these main uncertainties. Mitigation decisions are made while acknowledging the specified uncertainties, anticipated learning and the possibility to determine subsequent mitigation efforts in a sequential manner.

Three separate issues are addressed. First, the results portray how the consideration of uncertainty and learning regarding two main sources of uncertainty affects the outcomes of CBA. Second, the sensitivity analysis portrays how divergent the policy guidance gained from CBA can be, given the range of plausible parametrizations. Last, the results are reflected in relation to the Paris Agreement targets, discussing whether the targets are supported by the analysis presented here.

2. Methods

Scenarios are calculated with SCORE (Ekholm et al., 2013; Ekholm, 2014; Ekholm and Korhonen, 2016), a lightweight IAM with stochastic capabilities. A graphical overview of the model is presented in Fig. 1 and a more detailed description in the Supplementary material.

The objective of the model is to minimize the expected present value of mitigation costs and climate damages in long-term scenarios. Mitigation costs are portrayed through emission reduction cost curves, while climate damages are a function of temperature change. Uncertainty and learning over climate sensitivity and damages is described with scenario trees. Future costs and damages are discounted with rates of 1%, 3% and 5% in different cases, reflecting the range used in past prominent climatic cost-benefit analyses (Dasgupta, 2008).[2]

The marginal abatement cost curves were updated from the earlier versions of the model. The new cost curves are based on a multi-model study on the Shared Socioeconomic Pathways (SSPs) (Riahi et al., 2017): 82 scenarios with five different storylines and five climate policy cases, run with six large-scale IAMs. A single curve of the form $R_t = \alpha_t\, c_t^{\beta_t}$, where R_t is the emission reduction and c_t the marginal reduction cost at time t, was fitted in the middle of the scenarios' emission-marginal cost space for the year 2020. To reflect the broad range of future marginal costs in the scenarios, two sets of curves with either high or low costs were used beyond 2020, matching approximately to the higher and lower envelopes of the SSP scenario results. See the Supplementary material for details. As SCORE is implemented with the TIMES modeling framework (Loulou, 2008) employing linear programming, the curves are split into 100 discrete steps to allow a linear formulation.

Climate damages are based on the 2016 version of the DICE model (Nordhaus, 2017). Damages $D(t,\Delta T)$ are represented as a function of temperature change ΔT: $D(t,\Delta T) = Y(t)\ a\ \Delta T^b$, where $Y(t)$ is the world gross economic output. In SCORE, $Y(t)$ is defined exogenously and corresponds to the DICE optimal policy scenario, in which global per capita output grows by roughly 2% per annum between 2015 and 2100.

[2] In common economic models used in this context, the social discount rate comprises of a pure rate of time preference and a rate of risk aversion, and prominent past analyses have used discount rates ranging from 1.4% to 4.4% (Dasgupta, 2008; Nordhaus, 2017).

The differences in output $Y(t)$ between alternative DICE scenarios are small, below 1% up to the year 2100; and thus the exogenous economic output assumption in SCORE reproduces fairly accurately the climate damages of DICE with respect to a certain future development of temperature change. While this exogenous growth assumption involves a caveat of disregarding a feedback between climate damages and economic growth, this feedback becomes significant only in the long-run if climate damages inflict significant damages to economic output. The damage calculations is nevertheless an underestimation due to this simplification.

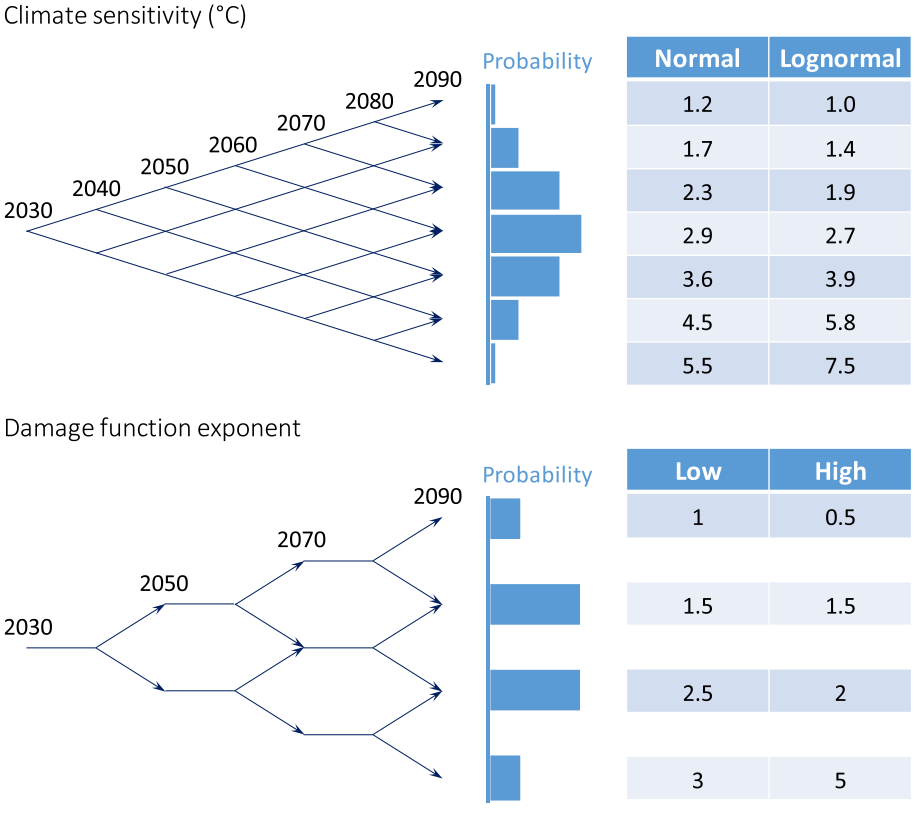
The DICE damage function is parametrized as $a = 0.00236$ and $b = 2$, which has been calibrated so that the damages are 2.1% of global income at temperature change 3 °C (Nordhaus, 2017). Yet it has been acknowledged early on (Nordhaus, 1991) that these parameters are highly uncertain; in particular that we know very little about the shape of the damage function, which is expressed through the exponent b. This motivates the analysis of climate damage risks by adding uncertainty to the damage exponent.

Uncertainties are considered in the model by assuming a discrete probability distribution and exogenously defined process of perfect learning for each uncertain parameter. The scenario trees for climate sensitivity and damage parameters, presented in Fig. 2, are binomial lattices with 50% branching probabilities every 10 or 20 years. In essence, they represent a binomial probability distribution and a learning process that sequentially excludes either the highest or the lowest value of the prevailing probability distribution at each branching point, after which the probability distribution is again binomial but with a shifted weight of the probability mass. An interesting feature of this approach is that it allows temporary negative learning (Oppenheimer et al., 2008) to take place. Two alternative probability distributions are used for both factors, representing the uncertainty underlying the uncertainty estimates themselves. Scenarios with no learning are also calculated for reference.

The representation of uncertainty in climate sensitivity is the same as with earlier applications of SCORE (Ekholm, 2014), although the learning process has been postponed by 10 years and a new, more fat-tailed uncertainty distribution has been added as an alternative case. Six branching points are assumed with 10-year intervals, starting from the year 2040, which lead to seven end-states for climate sensitivity and that the exact value is known in the year 2090. The probability distributions are discretized versions of the normal and lognormal distributions presented earlier (Knutti and Hegerl, 2008), while the pace of learning corresponds to estimates using Bayesian inference (Webster et al., 2008; Urban et al., 2014). Somewhat longer learning timeframes have been reported in other studies, but different formulations make a direct comparisons difficult. Kelly and Tan (2015) estimate that the uncertainty could be narrowed to 5% in 85 years, although extreme values are ruled out much earlier; while Hwang et al. (2017) report learning to be slower. The impact of a slower learning assumption can be nevertheless estimated from scenarios that include no learning.

For climate damages, a similar approach is used, but only with three branchings and 20-year intervals, thus leading to four end-states by 2090. The lower number of branchings is motivated by the assumption that attribution and learning on climate damages is harder than measurement of climate sensitivity based on new observations, but also due to computational limitations. Two mean-preserving spreads are assumed – both entirely conjectural – to represent the possibilities of lower and higher climate damage risks. Although both distributions keep the damage exponent's expected value at 2, the additional convexity of the damage function resulting from the distributions implies higher expected climate damages with temperature change above 1 °C. The parameter values for the probability distributions are presented in Fig. 2.

The uncertainty over climate damages should be interpreted to represent the uncertainty in the physical impacts, not on how these impacts are valued, as the exogenous learning can be reasonably assumed for the physical impacts only. The valuation of different impacts can, nevertheless, affect the uncertainty. Climate change will have diverse



Normal	Lognormal
1.2	1.0
1.7	1.4
2.3	1.9
2.9	2.7
3.6	3.9
4.5	5.8
5.5	7.5

Low	High
1	0.5
1.5	1.5
2.5	2
3	5

Fig. 2. The learning processes and binomial probability distributions assumed for climate sensitivity (top) and the exponent of the climate damage function (bottom). The binomial lattices and distributions are equal in all parametrizations of the model, but the parameter value associated with each end-state is varied between cases. The parameter values for normal and lognormal probability distributions for the climate sensitivity, and low and high distributions for the damage function exponent, are presented on the right.

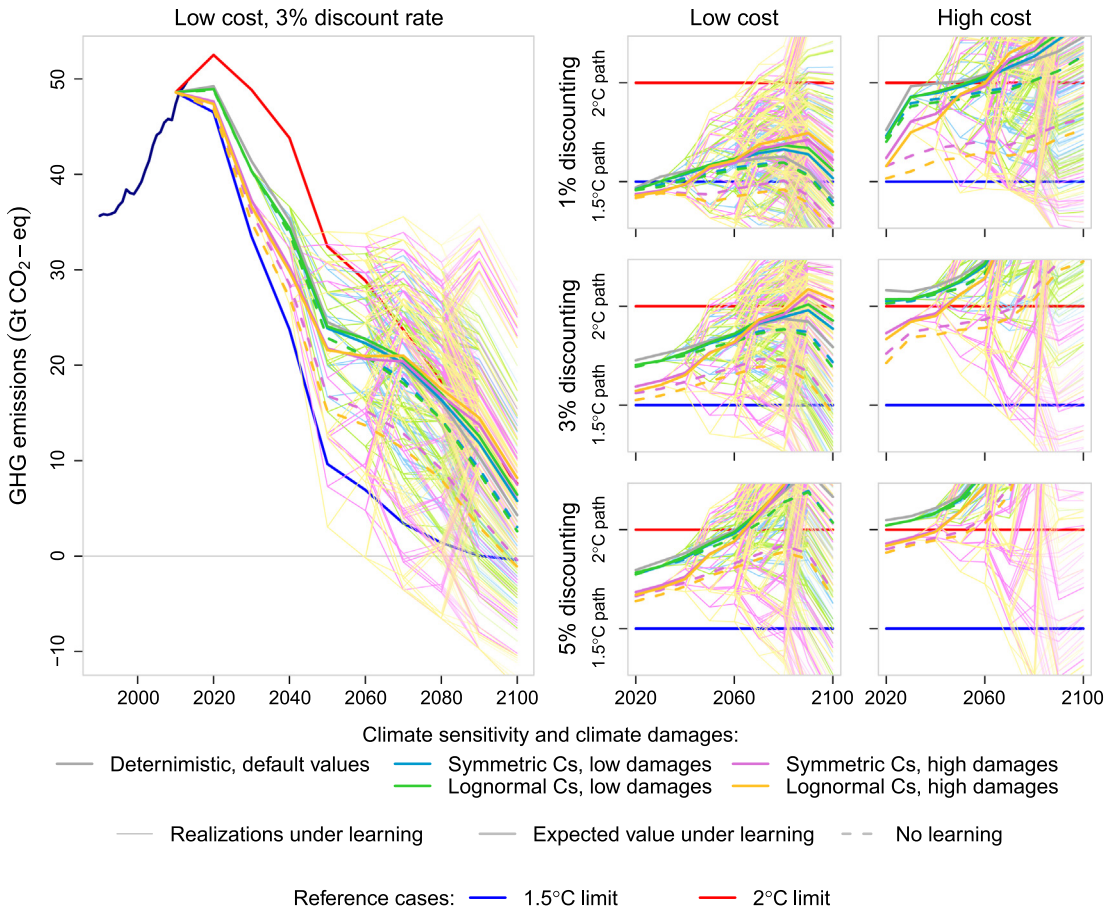


Fig. 3. Optimal greenhouse gas emission pathways, in absolute amounts (left) or scaled to cost-efficient 1.5 °C and 2 °C pathways (right), with different parametrizations. Alternative discount rates and future mitigation cost assumptions are covered in the scaled pathways on the right. Uncertainty assumptions for climate sensitivity and damages are represented with line color. Thin lines indicate different future realizations under learning and sequential decision-making, while a thick line represents the mean of these realizations. Dashed lines indicate a scenario where no learning on the uncertainties takes place. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

effects in different parts of the globe. Therefore, higher economic damages, for example, can be realized if the physical impacts' overall magnitude is found out to be higher, or if the physical impacts with higher damage valuation are found out to be more prevalent than those with lower valuation.

SCORE finds the optimal emission pathways so that the expected net present value of mitigation costs and climate damages are minimized. The model is run in 10 year timesteps up to year 2200, but most of the results are presented only up to 2100. The two binomial lattices yield 512 possible realizations for the learning process, and hence the resulting sequentially readjusted emission pathways also have the form of a scenario tree with 512 branches. The optimization problem minimizes the discounted costs and damages over the set of scenario branches, while non-anticipativity constraints require that the emission reductions are equal across branches that are in the same information state.

3. Results

Optimal probabilistic emission pathways with alternative parametrizations are presented in Fig. 3. The left panel shows cases with a 3% discount rate and low mitigation costs in terms of actual greenhouse gas emissions. Two corresponding deterministic cases that keep temperature below 1.5 °C or 2 °C in a cost-efficient manner under a best-guess climate sensitivity (3 °C) are also presented for reference.

On the right side of the figure, the emission pathways with different discount rate and mitigation cost assumptions have been scaled linearly to the respective cost-efficient 1.5 °C and 2 °C trajectories.[3] This representation could be called a *temperature path index*. Note that the cost-efficient trajectories depend on the discount rate and mitigation cost, and hence do not match exactly to the blue and red trajectories on the left panel.

While the optimal emission pathways vary considerably between the cases and realizations, emission levels for the next decades fall between the 1.5 °C and 2 °C trajectories in nearly all of the calculated cases. Only cases with low mitigation costs and 1% discounting start lower than the corresponding 1.5 °C trajectory, while cases with high costs, 3% or 5% discounting and lower distribution for damages start higher than the 2 °C trajectories.

These results thus suggest that, as next decades' mitigation efforts are considered, the 1.5–2 °C target range of the Paris Agreement is consistent with the cost-benefit approach under a wide range of plausible parameter choices. This could be contrasted with earlier analyses with the DICE model that have suggested optimal emissions pathways that increase for several decades and result in temperature increase well exceeding 3 °C (Nordhaus, 2017), even when accounting for uncertainty

[3] That is, if $E_{1.5,t,d,c}$ and $E_{2,t,d,c}$ are the emission levels in year t in two cost-efficient deterministic scenarios that limit temperature change to 1.5 °C and 2 °C, both having discounting rate d and mitigation costs of c, then the emissions $E_{t,d,c}$ in a stochastic scenario with the same discount rate and mitigation costs are represented as $1.5 + 0.5\ (E_{1.5,t,d,c} - E_{t,d,c})/(E_{1.5,t,d,c} - E_{2,t,d,c})$.

in climate damages (Crost and Traeger, 2014). One important factor behind this difference is the assumption for future mitigation costs, as the SSP scenarios project far deeper emission cuts to be achievable with a certain price level than what DICE assumes. On the other hand, the result's range of greenhouse gas emissions in 2030 is similar to a recent compilation of 1.5–2 °C emission scenarios, although somewhat broader; and also imply that the currently planned mitigation efforts under the Paris Agreement are not ambitious enough (Rogelj et al., 2016).

After 2030, when the assumed learning process starts, the emission pathways start to diverge strongly due to the readjustments to the mitigation strategy following new information. Each branching in the scenario tree towards higher climate sensitivity or damages leads to stronger emission reductions than the branching towards lower higher climate sensitivity and damages. As a result, the lowest emission levels during the latter half of the century arise in realizations where sensitivity and damages are found out to be high. Notable emission reductions are, however, carried out even with the lowest realizations, as the mitigation cost assumptions imply that such reductions could be achieved with relatively modest marginal costs towards the end of the century.

The scenarios also exhibit a number of past observations. If future learning on climate sensitivity and damages is excluded, which is presented with dashed lines in Fig. 3, it will be optimal to mitigate more than under expected learning (Hwang et al., 2017). Uncertainty in climate sensitivity has very minor impact on optimal mitigation if the climate damages are only moderate, but the effect of climate sensitivity is amplified considerably if catastrophic climate damages are deemed possible (Ackerman et al., 2010; Calel et al., 2013), implying that the existence of fat tails can dominate the optimal policy response (Weitzman, 2009).

In the ideal CBA setting, the marginal cost of reducing emissions equals the social cost of carbon: the expected present value of damages due to a marginal increase in emissions. The evolution of such carbon pricing follows a pattern similar to the emission pathways in the scenarios with uncertainty and learning: a gradually increasing price that starts to diverge due to learning and readjustments in the mitigation strategy. That is, the adaptive mitigation strategy leads to volatility in the future carbon price.

The change in global mean temperature, on the other hand, is affected by emission reductions in each scenario branch, but also by the true level of climate sensitivity in that particular branch. Whereas carbon pricing thus exhibits exactly the same scenario tree structure than the emission pathways, the temperature pathways start to diverge due to changes in climate sensitivity.

The evolution of carbon prices and global temperature change are illustrated in Fig. 4 for cases with 3% discounting and low mitigation costs, and discussed further below for all calculated cases. The highest carbon prices in the figure arise with scenario branches where both climate sensitivity and damages turn out to be high, while the lowest prices correspond to both low sensitivity and damages. The temperature change is more dominated by the value of climate sensitivity in each scenario branch, which is visible from the early-on separation of the branches with differing values of climate sensitivity.

To further analyze carbon prices, Fig. 5 presents the price in 2030, volatility and the growth rate of the expected carbon price between 2030 and 2100 under all parametrizations. The left pane exhibits a strong inverse relationship between the 2030 level and the future growth rate of the carbon price. With a lower discount rate the carbon price starts higher but is expected to grow more slowly. Assuming a greater level of uncertainty produces a similar effect than a smaller discount rate. The higher uncertainty assumption for damages adds a 30% to 95% risk component to the 2030 carbon price compared to cases with lower uncertainty, and this effect is more pronounced with higher costs and a higher discount rate. Higher mitigation costs lead to high relative increases in 2030 carbon prices and growth rates, particularly under 1% discounting and higher damage uncertainty.

Discounting and mitigation costs have only a minor impact on the volatility of the carbon price between 2030 and 2100, however, which is mostly determined by the uncertainty assumption for climate damages. The volatility from 2030 to 2050 is somewhat higher than until 2100, with the maximum of calculated cases around 25%. The carbon price volatility during the next decades can, therefore, be of similar magnitude to stock price volatilities due to the considered uncertainties. It seems yet worth to note that the source and structure of these volatilities is very different, as the volatility modelled here is due to resolution of scientific uncertainties on a decadal timescale.

The readjustment of mitigation strategies under learning can lead to diverse levels at which the global mean temperature increase would be optimally stabilized. This is represented in Fig. 6 via temperature levels in the year 2200, although the temperature might not have fully stabilized by that time in some of the scenario branches. The temperature is presented in each sub-figure with respect to two parameters – the realized climate sensitivity or damage exponent, or the chosen discount rate and cost level – and averaged over the remaining two parameters.

The highest stabilization temperatures, exceeding 4 °C, are a result of high climate sensitivity combined with low damages or high reduction costs. It is worth noting that while a higher realization of climate sensitivity leads to higher stabilization temperature, it also renders higher mitigation efforts optimal, which alleviate the increase in temperature. Conversely, the lowest stabilization temperature, below 1.5 °C, occur with low climate sensitivity, high damages and low mitigation costs. The discount rate assumption has only a minor impact on the stabilization temperature.

A comparison with the next decades' optimal emission pathways in Fig. 3 yields an interesting conclusion. Although it would be optimal to follow emission pathways between the cost-efficient 1.5 °C and 2 °C trajectories for the next decades, readjustments to mitigation strategy following new information can make it optimal to revise also the temperature targets over the current and next century, possibly leading to a level that differs notably from the 1.5 °C to 2 °C range. Temperature targets can be a useful signaling device for next decades' mitigation objectives, but considering the targets as immutable is not an optimal way to frame climate policy.

4. Discussion

The focal question posed in the introduction was whether a cost-benefit analysis is applicable in the climatic setting, given the large uncertainties involved. Uncertainty can certainly be taken into account in the analyses (Golub et al., 2014). By testing alternative plausible specifications for the uncertainties, the research presented here was able to find relatively solid policy guidance for near-term emission pathways, concomitantly making evident how robust the conclusions actually are. Yet, this approach does not remove the lack of knowledge, and the climatic cost-benefit analyses might be inevitably based on conjectural assumptions. Some of the results, such as those on carbon price volatility, were highly sensitive to the specified uncertainty.

As a corollary, whether CBA can provide policy guidance that is sufficiently stable across plausible parameterizations depends on what kind of policies are being guided. Conclusions regarding some results could be narrowed down better than on others. The emission pathways scaled to the temperature path index were more insensitive to the assumptions, because the temperature-constrained emission pathways on which the scaling is based on reacted in a similar manner to the discount rate and mitigation cost assumptions (see Ekholm, 2014) than the emission pathways based on cost-benefit analysis. However, the estimates for social cost of carbon were highly divergent across the assumptions employed, as were the long-term temperature targets due to the uncertainties. This seems rather obvious. If the risks are not well known and impacts are hard to value, it is evident that one cannot place a solid price for them.

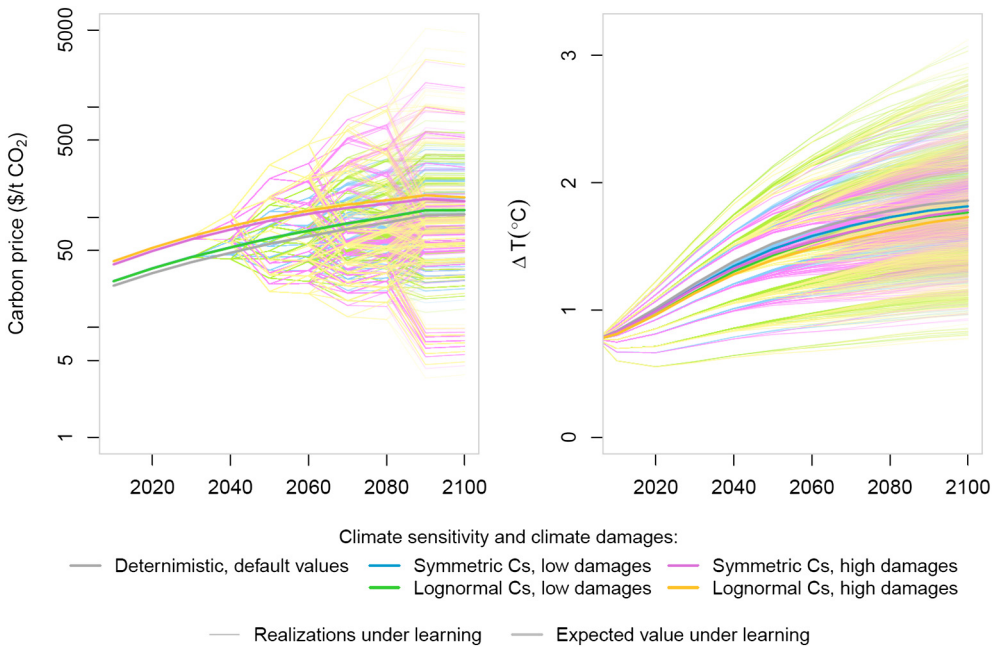


Fig. 4. The Social Cost of Carbon and the change in global mean temperature up to 2100 in scenarios with 3% and low mitigation costs.

The practical policy guidance that can be inferred from the results is that the Paris Agreement temperature target range is a good guideline for the next decades' mitigation under a wide range of plausible parametrizations. The results thus also call for strengthening the response for mitigating climate change, as there is a clear gap between countries' current policies and the long-term targets of the Agreement (Rogelj et al., 2016). New information is, however, gradually gained on climate sensitivity, the impacts of climate change and mitigation costs. Consequently, the temperature target range should not be seen as immutable, but refined or narrowed-down based on this new information.

A deterministic cost-benefit analysis on climate change mitigation would disregard the role of risks in the valuation of climate change, while using only single parametrization would give a false sense of precision. Relying complacently on such analysis would be both misguided and fallacious.

Incorporating uncertainty, learning and sequential decision-making provides a more realistic representation of the climatic problem. Consideration of uncertainty affects how climate change is valued and, furthermore, enables the assessment of novel aspects, such as carbon price volatility or revisions to the temperature targets. Additional refinements could be yet made regarding how the learning is represented. One caveat in the approach used is that the most severe outcomes are ruled out relatively early on some scenario branches, a process termed as tail-learning (Kelly and Tan, 2015).

A few of important aspects in the climate change problem setting were also omitted here. Uncertainty in the transient climate response

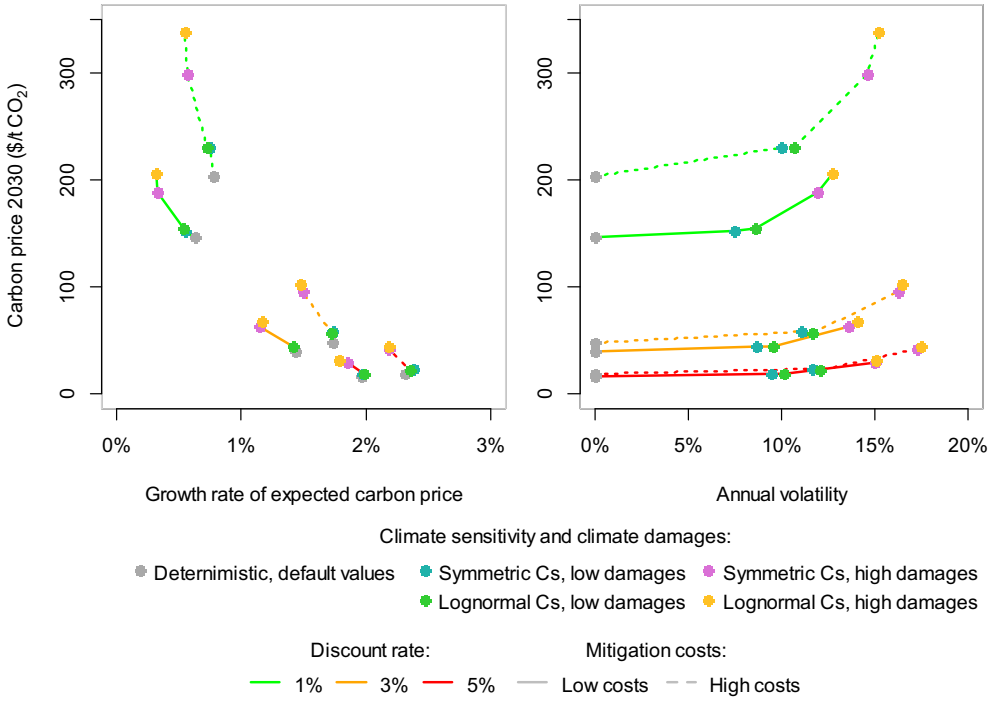


Fig. 5. The Social Cost of Carbon (SCC) in 2030 prior to the assumed learning (y-axes), the growth rate for the expected value of SCC between 2030 and 2100 (left panel, x-axis) and the volatility of the SCC between 2030 and 2100 due to the assumed learning (right panel, x-axis) with different assumptions on uncertainty on climate sensitivity and damages (dot color), discount rate (connecting line color) and future mitigation costs (connecting line type). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

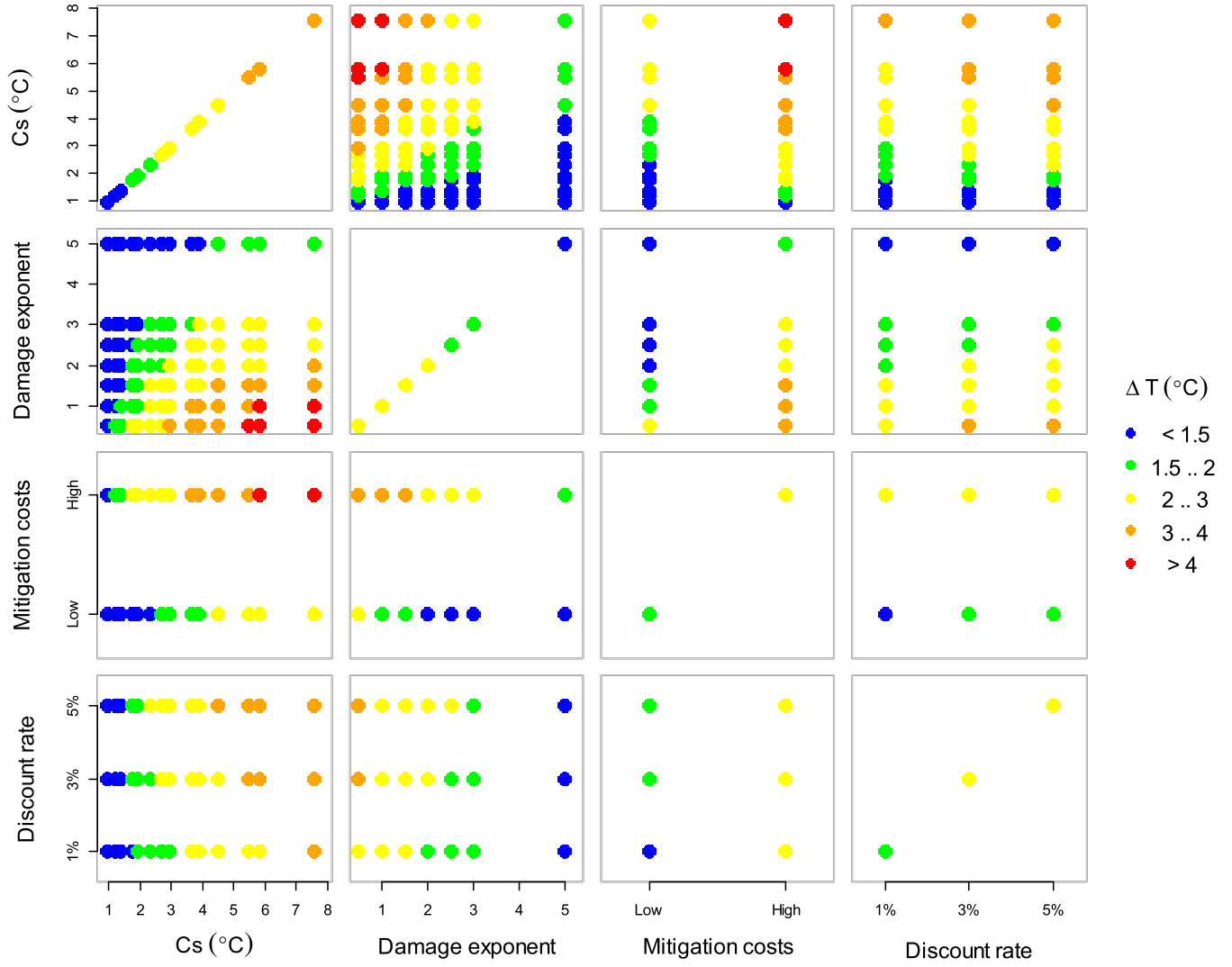


Fig. 6. Global mean temperature change in 2200 in the stochastic scenarios. Temperature is represented with color, plotted pairwise with respect to two parameters (rows and columns of the plots) and averaged over the remaining two parameters. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(Shindell, 2014) was captured only indirectly here through equilibrium climate sensitivity. Tipping points are an additional risk factor that is critical to consider when determining mitigation strategies (Cai et al., 2016; Lemoine and Traeger, 2016). Also, mitigation measures that do not affect emissions, such as solar radiation management, could be considered (Ekholm and Korhonen, 2016).

On a broader level, it is critical to note that idealized models such as SCORE employ an aggregate representation of decision-making and utility, which does not correspond to reality. The optimization does not consider how mitigation costs or climate damages are distributed, although this can affect the valuation of climate change impacts (Schmidt et al., 2013; Adler et al., 2017). The social optimality of cost-benefit framework is often maintained by an implicit assumption that individuals compensate each other for possible losses. The model cannot answer whether this would take place in practice.

Improved understanding on climatic change will enable more comprehensive climate damage assessments, which have previously overlooked many potential impacts (van den Bergh and Botzen, 2014, 2015). Indeed, such process is a prerequisite for the learning on climate damages that was considered in this paper. Further analyses could also expand from the prevalent approach of using temperature change as a proxy for climate damages, possibly showing that other targets apart from temperature are also necessary, which – in turn – has been proposed to warrant higher mitigation effort (Steinacher et al., 2013). While the critique of past analyses has been discerning, future research can certainly overcome past shortcomings. This exercise is one contribution towards that direction.

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Appendix A. Supplementary Material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.ecolecon.2018.07.024.

References

Ackerman, F., Stanton, E.A., Bueno, R., 2010. Fat tails, exponents, extreme uncertainty: simulating catastrophe in DICE. Ecol. Econ. 69, 1657.
Adler, M., Anthoff, D., Bosetti, V., Garner, G., Keller, K., Treich, N., 2017. Priority for the worse-off and the social cost of carbon. Nat. Clim. Chang. 7, 443–449.
Cai, Y., Lenton, T.M., Lontzek, T.S., 2016. Risk of multiple interacting tipping points should encourage rapid CO_2 emission reduction. Nat. Clim. Change 6, 520–525.

Calel, R., Stainforth, D.A., Dietz, S., 2013. Tall tales and fat tails: the science and economics of extreme warming. Clim. Chang. 132, 127–141.
Crost, B., Traeger, C.P., 2014. Optimal CO_2 mitigation under damage risk valuation. Nat. Clim. Chang. 4, 631–636.
Crowards, T.M., 1998. Safe minimum standards: costs and opportunities. Ecol. Econ. 25, 303–314.
Dasgupta, P., 2008. Discounting climate change. J. Risk Uncertain. 37, 141–169.
Ekholm, T., 2014. Hedging the climate sensitivity risks of a temperature target. Clim. Chang. 127, 153–167.
Ekholm, T., Korhonen, H., 2016. Climate change mitigation strategy under an uncertain solar radiation management possibility. Clim. Chang. 139, 503–515.
Ekholm, T., Lindroos, T.J., Savolainen, I., 2013. Robustness of climate metrics under climate policy ambiguity. Environ Sci Policy 31, 44–52.
Golub, A., Narita, D., Schmidt, M.G.W., 2014. Uncertainty in integrated assessment models of climate change: alternative analytical approaches. Environ. Model. Assess. 19, 99–109.
Hall, J.W., Lempert, R.J., Keller, K., Hackbarth, A., Mijere, C., McInerney, D.J., 2012. Robust climate policies under uncertainty: a comparison of robust decision making and info-gap methods. Risk Anal. 32, 1657–1672.
Hwang, I.C., Reynès, F., Tol, R.S.J., 2017. The effect of learning on climate policy under fat-tailed risk. Resour. Energy Econ. 48, 1–18.
Kelly, D.L., Tan, Z., 2015. Learning and climate feedbacks: optimal climate insurance and fat tails. J. Environ. Econ. Manag. 72, 98–122.
Knutti, R., Hegerl, G.C., 2008. The equilibrium sensitivity of the earth's temperature to radiation changes. Nat. Geosci. 1, 735–743.
Kolstad, C.D., 1996. Learning and stock effects in environmental regulation: the case of greenhouse gas emissions. J. Environ. Econ. Manag. 1–18.
Lave, L.B., Dowlatabadi, H., 1993. Climate change: the effects of personal beliefs and scientific uncertainty. Environ. Sci. Technol. 27, 1962–1972.
Leach, A.J., 2007. The climate change learning curve. J. Econ. Dyn. Control. 31, 1728–1752.
Lemoine, D., Traeger, C.P., 2016. Economics of tipping the climate dominoes. Nat. Clim. Change 6, 514–519.
Lempert, R.J., Schlesinger, M.E., Bankes, S.C., 1996. When we don't know the costs or the benefits: adaptive strategies for abating climate change. Clim. Chang. 33, 235–274.
Loulou, R., 2008. ETSAP-TIAM: the TIMES integrated assessment model. Part II: mathematical formulation. Comput. Manag. Sci. 5, 41–66.
Nordhaus, W.D., 1991. To slow or not to slow: the economics of the greenhouse effect. Econ. J. 101, 920–937.
Nordhaus, W.D., 2017. Revisiting the social cost of carbon. Proc. Natl. Acad. Sci. 114, 1518–1523.
Oppenheimer, M., O'Neill, B.C., Webster, M., 2008. Negative learning. Clim. Chang. 89, 155–172.
Pindyck, R.S., 2013. Climate change policy: what do the models tell us? J. Econ. Lit. 51, 1–23.
Plambeck, E.L., Hope, C., 1996. PAGE95: an updated valuation of the impacts of global warming. Energy Policy 24, 783–793.
Randalls, S., 2010. History of the 2 °C climate target. Wiley Interdiscip. Rev. Clim. Chang. 1, 598–605.
Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Glob. Environ. Chang. 42, 153–168.
Rogelj, J., McCollum, D.L., Reisinger, A., Meinshausen, M., Riahi, K., 2013. Probabilistic cost estimates for climate change mitigation. Nature 493, 79–83.
Rogelj, J., den Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., Schaeffer, R., Sha, F., Riahi, K., Meinshausen, M., 2016. Paris Agreement climate proposals need a boost to keep warming well below 2 °C. Nature 534, 631–639.
Schmidt, M.G.W., Held, H., Kriegler, E., Lorenz, A., 2013. Climate policy under uncertain and heterogeneous climate damages. Environ. Resour. Econ. 54, 79–99.
Shindell, D.T., 2014. Inhomogeneous forcing and transient climate sensitivity. Nat. Clim. Chang. 4, 274–277.
Steinacher, M., Joos, F., Stocker, T.F., 2013. Allowable carbon emissions lowered by multiple climate targets. Nature 499, 197–201.
Tol, R.S.J., 2009. The economic effects of climate change. J. Econ. Perspect. 23, 29–51.
Urban, N.M., Holden, P.B., Edwards, N.R., Sriver, R.L., Keller, K., 2014. Historical and future learning about climate sensitivity. Geophys. Res. Lett. 41, 2543–2552.
van den Bergh, J.C.J.M., Botzen, W.J.W., 2014. A lower bound to the social cost of CO_2 emissions. Nat. Clim. Chang. 4, 253–258.
van den Bergh, J.C.J.M., Botzen, W.J.W., 2015. Monetary valuation of the social cost of CO_2 emissions: a critical survey. Ecol. Econ. 114, 33–46.
Webster, M., Jakobovits, L., Norton, J., 2008. Learning about climate change and implications for near-term policy. Clim. Chang. 89, 67–85.
Weitzman, M.L., 2009. On Modeling and interpreting the economics of catastrophic climate change. Rev. Econ. Stat. 91, 1–19.
Yohe, G., 1996. Exercises in hedging against extreme consequences of global change and the expected value of information1. Glob. Environ. Chang. 6, 87–101.